



Harvard John A. Paulson  
School of Engineering  
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# The Concurrent Composition of Differential Privacy

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Master Thesis Project at Harvard University  
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# Outline



- Background
- Definitions and Basic Properties
- Concurrent Composition for Pure Interactive Differential Privacy
- Concurrent Composition for Approximate Interactive Differential Privacy
- Characterization of Concurrent Composition
- Empirical Findings & Future Work

# Outline

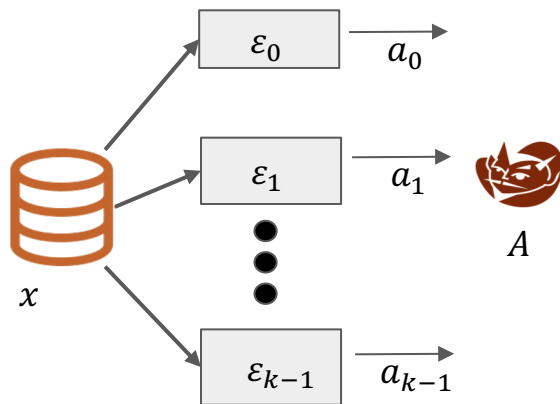


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# Background: DP under Composition

- Goal: analyze the privacy loss under the composition of multiple different mechanisms on the same dataset
  - Rarely want to release only a single statistic about a dataset.
  - Useful tool in algorithm design.
  - If the building blocks are proven to be private, it would be easy to reason about privacy of a complex algorithm built on these building blocks.





# Background: DP under Composition

- Basic composition: If  $M_i$  is  $(\varepsilon, \delta)$  -DP for  $i = 0, \dots, k - 1$ , then  $M(x) = (M_0(x), \dots, M_{k-1}(x))$  is  $(k\varepsilon, k\delta)$  -DP.
  - The randomness of  $M_i$  are independent to each other.
- Advanced composition: If  $M_i$  is  $(\varepsilon, \delta)$  -DP for  $i = 0, \dots, k - 1$ , then  $M(x) = (M_0(x), \dots, M_{k-1}(x))$  is  $(O(\sqrt{k \log(\frac{1}{\delta'})}) \varepsilon, k\delta + \delta')$ -DP.
  - The randomness of  $M_i$  are independent to each other.
- Optimal Composition [KOV15, MV16]
- Moment accountant [ACGMMTZ16]



# Interactive Differential Privacy

- Many of the useful differential privacy primitives are actually interactive mechanisms, which allow one to ask an adaptive sequence of queries about the dataset.
  - e.g., **Sparse Vector Technique (SVT)**    **Many applications!**

*Input:  $q_1, \dots, q_i, \dots, q_\infty$*

*If  $q_i + \text{Noise} > T_i + \text{Noise}$ , output  $T$ ;*

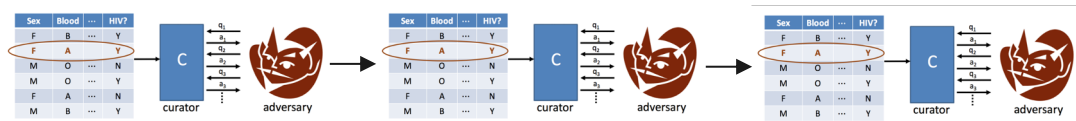
*else output  $\perp$ .*

*\*  $c$  # number of  $T$  (Privacy cost is proportional to  $\sqrt{c}$ )*



# Interactive DP under Composition

- There could be more than one composition operations for interactive mechanisms.
- **Sequential Composition:** all of the queries to the current mechanism must be completed before the interaction with another mechanism can be spawned.



- **Concurrent Composition:** multiple interactions can be spawned and be executed simultaneously, queries to the mechanisms can be arbitrarily interleaved.





# Main Results

- Group Privacy-like bound  $(k\varepsilon, ke^{k\varepsilon}\delta)$  for the concurrent composition of approximate interactive DP mechanisms.
- Characterize arbitrary **pure** interactive DP mechanism as the interactive post-processing of randomized response (a non-interactive mechanism).
- **=> Optimal bound** for the concurrent composition of pure interactive DP.
- **Based on computer simulation, we conjecture that optimal composition bound may extend to approximate DP.**





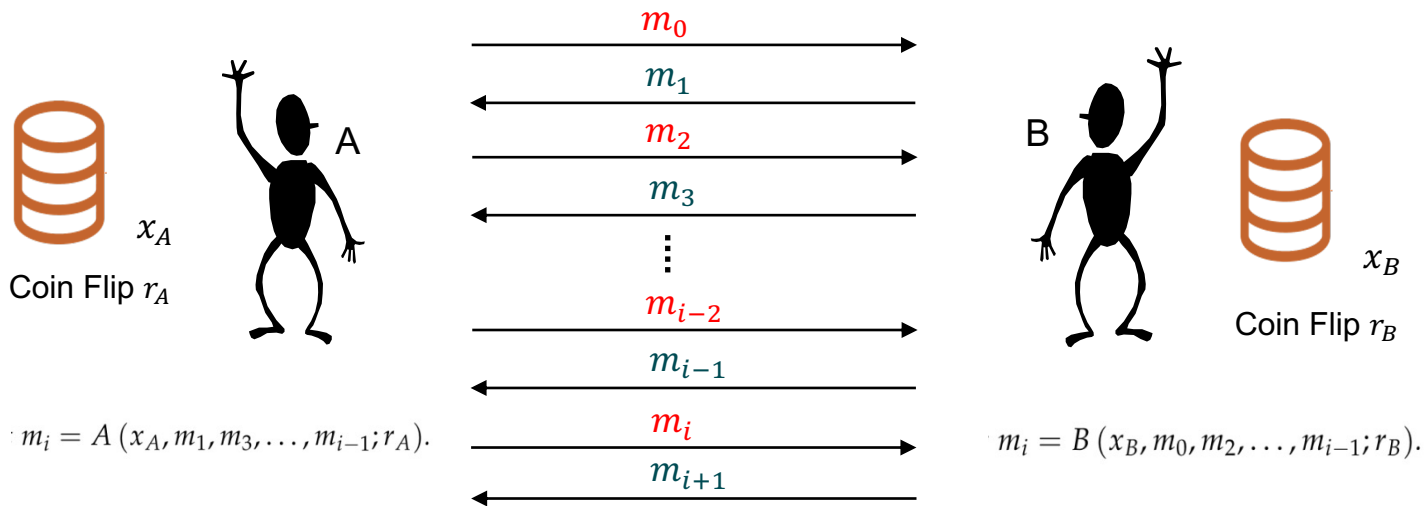
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# Formalization: interactive protocol

- Interactive Protocol between two parties A and B
  - Each party as a function
  - (private input, received messages, random coins) => Next message to be sent out





# Formalization: view of a party

$$\text{View}_A \langle A(x_A), B(x_B) \rangle = (r_A, x_A, \underline{m_1, m_3, \dots})$$

Randomness   Private Input   received messages

- In our case, party A is the adversary and party B is an interactive mechanism whose input is dataset  $x$ .
- Since we will only be interested in the adversary's view and the adversary does not have an input, we will drop the subscript and write A's view as  $\text{View} \langle A, B(x) \rangle$



# Formalization: interactive differential privacy

- The interactive differentially privacy as a type of interactive protocol between an adversary (without any computational limitations) and an interactive mechanism of special properties.

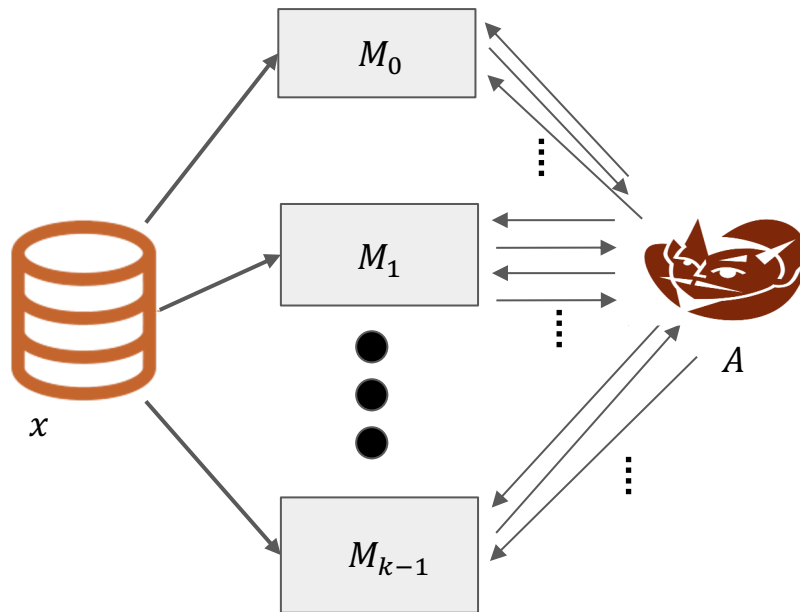
**Definition 4** (Interactive Differential Privacy). *A randomized algorithm  $\mathcal{M}$  is  $(\epsilon, \delta)$ -differentially private interactive mechanism if for every pair of adjacent datasets  $x, x'$ , for every adversary algorithm  $\mathcal{A}$ , for every possible output set  $T \subseteq \text{Range}(\text{View}\langle \mathcal{A}, \mathcal{M}(\cdot) \rangle)$  we have*

$$\Pr[\text{View}\langle \mathcal{A}, \mathcal{M}(x) \rangle \in T] \leq e^\epsilon \Pr[\text{View}\langle \mathcal{A}, \mathcal{M}(x') \rangle \in T] + \delta$$



# Concurrent Composition

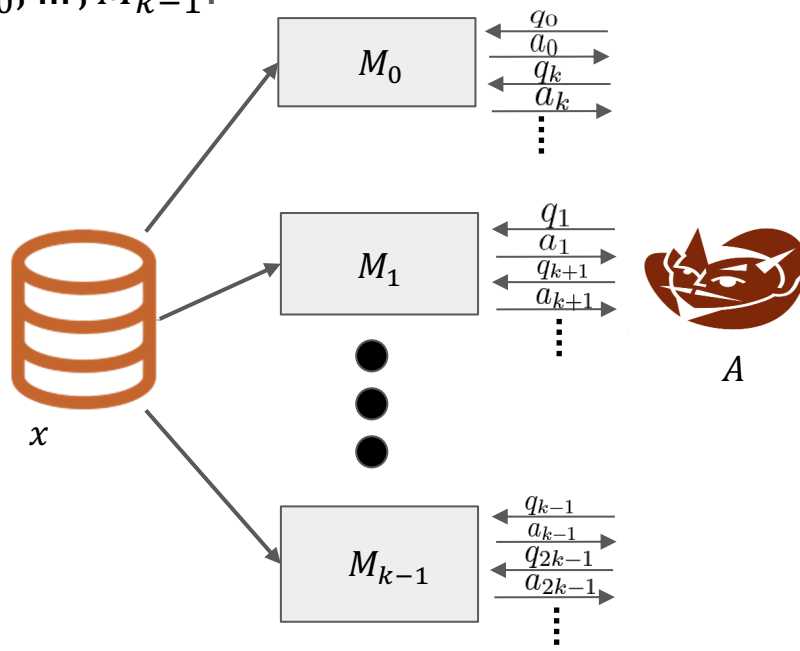
- We use  $ConComp(M_0, \dots, M_{k-1})$  to denote the concurrently composed mechanism of  $M_0, \dots, M_{k-1}$ .





# Ordered Concurrent Composition

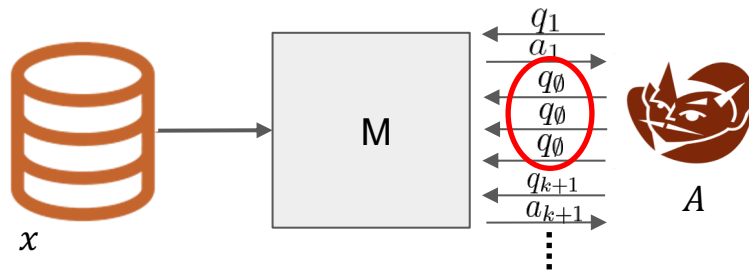
- For the convenience of the proof, we introduce a variant of concurrent composition of interactive protocols, which only accept queries **in the exact order** of  $M_0, \dots, M_{k-1}$ .





# Ordered Concurrent Composition

- We also introduce the **null query extension** of an interactive mechanism, which has the exact same output distribution of the original mechanism but also accept “dummy” query strings.





# Ordered Concurrent Composition

- Lemma: to prove  $ConComp(M_0, \dots, M_{k-1})$  is  $(\varepsilon, \delta)$ -DP, it suffices to prove the ordered concurrent composition of null query extensions of these mechanisms is also  $(\varepsilon, \delta)$ -DP.
  - Intuition: if the first query is sent to  $M_i$ , the second query is not sent to  $M_{i+1}$  but  $M_j$ , we can simply fill in dummy queries between  $M_i$  and  $M_j$ .
- $\Rightarrow$  We always assume the queries  $q_0, \dots, q_{k-1}, q_k, \dots, q_{\{2k-1\}}, \dots$  from adversary are sent to  $M_0, \dots, M_{k-1}$  **in order** in the proof, i.e.,  $q_\ell$  is sent to  $M_{\ell \bmod k}$ .
  - If an adversary  $A$  is concurrently interacting with two mechanisms  $M_0, M_1$ , we assume the queries **alternates** between them.





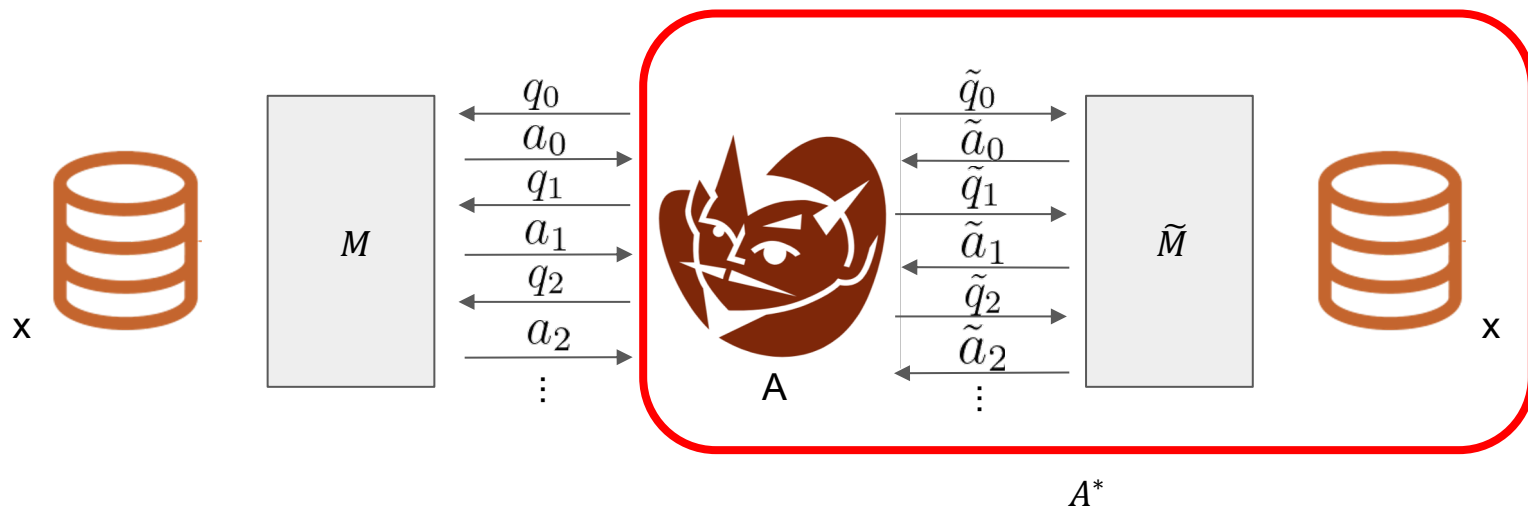
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# Concurrent Composition of Pure Interactive Differential Privacy

- Proof Sketch: view  $A$  and  $M$  as a combined adversary  $A^*$  interacting with  $\tilde{M}$





# Concurrent Composition of Pure Interactive Differential Privacy

- Proof Sketch: view  $A$  and  $M$  as a combined adversary  $A^*$  interacting with  $\tilde{M}$ 
  - $A^*$  is a well-defined strategy throughout the entire interactive session with  $M$ 
    - Randomness of  $A^*$ : the randomness of  $A$  and  $\tilde{M}$
    - Next-query function is also naturally defined:
      1. Random coin tosses for  $\mathcal{A}_{\tilde{\mathcal{M}}}^*(x)$  consist of  $r = (r_{\mathcal{A}}, r_{\tilde{\mathcal{M}}})$ .
      2.  $\mathcal{A}_{\tilde{\mathcal{M}}}^*(x)(a_0, a_1, \dots, a_{i-1}; r)$  is computed as follows:
        - (a)  $\tilde{q}_{i-1} = \mathcal{A}(a_0, \tilde{a}_0, \dots, a_{i-1}; r_{\mathcal{A}})$ , send to  $\tilde{\mathcal{M}}$ .
        - (b)  $\tilde{a}_{i-1} = \tilde{\mathcal{M}}(x, \tilde{q}_0, \tilde{q}_1, \dots, \tilde{q}_{i-1}; r_{\tilde{\mathcal{M}}})$ , send to  $\mathcal{A}$ .
        - (c)  $q_i = \mathcal{A}(a_0, \tilde{a}_0, \dots, a_{i-1}, \tilde{a}_{i-1}; r_{\mathcal{A}})$ .
        - (d) Output  $q_i$ .



# Concurrent Composition of Pure Interactive Differential Privacy

- Proof Sketch: view  $A$  and  $M$  as a combined adversary  $A^*$  interacting with  $\tilde{M}$ 
  - Given a transcript of  $A^*$ 's view, we can recover the view of  $A$  through post-processing, which is formulated as follows:

$\text{Post}(r_{\mathcal{A}}, r_{\tilde{\mathcal{M}}}, a_0, a_1, \dots, a_{T-1}; \mathcal{A}, \tilde{\mathcal{M}}(x)):$

1. For  $i = 1 \dots T - 1$ , compute

$$(a) \tilde{q}_{i-1} = \mathcal{A}(a_0, \tilde{a}_0, \dots, a_{i-1}; r_{\mathcal{A}})$$

$$(b) \tilde{a}_{i-1} = \tilde{\mathcal{M}}(x, \tilde{q}_1, \tilde{q}_2, \dots, \tilde{q}_{i-1}; r_{\tilde{\mathcal{M}}})$$

2. Output  $(r_{\mathcal{A}}, a_0, \tilde{a}_0, \dots, a_{T-1}, \tilde{a}_{T-1})$ .



# Concurrent Composition of Pure Interactive Differential Privacy

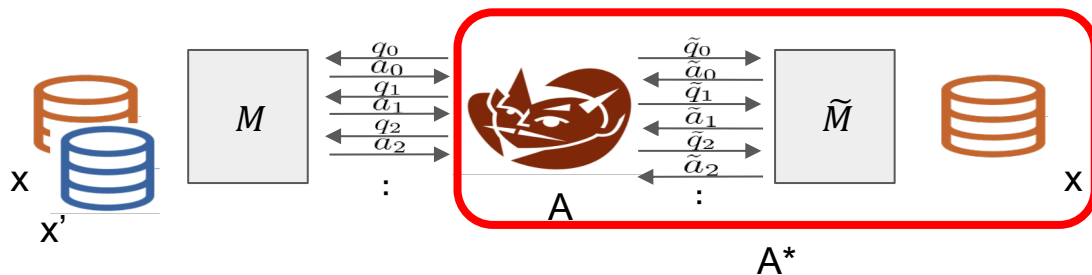
- Proof Sketch: view  $A$  and  $M$  as a combined adversary  $A^*$  interacting with  $\tilde{M}$ 
  - Given a transcript of  $A^*$ 's view, we can recover the view of  $A$  through post-processing.
  - For any event  $T$ , the probability that  $A$ 's view is in  $T$  is exactly equal to the probability that  $A^*$ 's view is in the inverse of the post-processing algorithm of event  $T$ .

$$\Pr [\text{View}\langle \mathcal{A}, \text{ConComp}(\mathcal{M}(x), \tilde{\mathcal{M}}(x)) \rangle \in T] = \Pr [\text{View}\langle \mathcal{A}_{\tilde{\mathcal{M}}}^*(x), \mathcal{M}(x) \rangle \in \text{Post}^{-1}(T)]$$



# Concurrent Composition of Pure Interactive Differential Privacy

- Proof Sketch: view  $A$  and  $M$  as a combined adversary  $A^*$  interacting with  $\tilde{M}$ 
  - Given a transcript of  $A^*$ 's view, we can recover the view of  $A$  through post-processing.
  - For any event  $T$ , the probability that  $A$ 's view is in  $T$  is exactly equal to the probability that  $A^*$ 's view is in the inverse of the post-processing algorithm of event  $T$ .
  - The random variable of  $A^*$ 's view enjoys differential privacy guarantee.





# Concurrent Composition of Pure Interactive Differential Privacy

- We say two random variables  $X$  and  $X'$  are  $(\epsilon, \delta)$ -indistinguishable if for every event  $T$  we have

$$\Pr[X \in T] \leq e^\epsilon \cdot \Pr[X' \in T] + \delta$$

$$\Pr[X' \in T] \leq e^\epsilon \cdot \Pr[X \in T] + \delta$$

- Denote as  $X \stackrel{(\epsilon, \delta)}{\approx} X'$
- Simple property: if  $X \stackrel{(\epsilon, 0)}{\approx} X'$ , and  $X' \stackrel{(\tilde{\epsilon}, 0)}{\approx} X''$ , then  $X \stackrel{(\epsilon + \tilde{\epsilon}, 0)}{\approx} X''$



# Concurrent Composition of Pure Interactive Differential Privacy

- Suppose  $M$  is  $(\epsilon, 0)$ -DP,  $\tilde{M}$  is  $(\tilde{\epsilon}, 0)$ -DP
- We know that  $\text{View}(A_{\tilde{M}(x)}^*, M(x))$  and  $\text{View}(A_{\tilde{M}(x)}^*, M(x'))$  are  $(\epsilon, 0)$ -indistinguishable.
- $\Rightarrow \text{View}(A, \text{ConComp}(M(x), \tilde{M}(x)))$  and  $\text{View}(A, \text{ConComp}(M(x'), \tilde{M}(x)))$  are  $(\epsilon, 0)$ -indistinguishable.
- Symmetrically, we have  $\text{View}(A, \text{ConComp}(M(x'), \tilde{M}(x))) \stackrel{(\tilde{\epsilon}, 0)}{\approx} \text{View}(A, \text{ConComp}(M(x'), \tilde{M}(x')))$
- Finally, we can bound the privacy of  $A$ 's view in the concurrent composition when the underlying dataset is  $x$  vs  $x'$ .

$$\text{View}(A, \text{ConComp}(M(x), \tilde{M}(x))) \stackrel{(\epsilon + \tilde{\epsilon}, 0)}{\approx} \text{View}(A, \text{ConComp}(M(x'), \tilde{M}(x')))$$



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# Concurrent Composition of Approximate Interactive Differential Privacy

- Suppose interactive mechanisms  $M_0, \dots, M_{\{k-1\}}$  are each  $(\epsilon_i, \delta_i)$ -differentially private.
- View  $A$  and  $M_0, \dots, M_{\{i-1\}}, M_{\{i+1\}}, \dots, M_{\{k-1\}}$  as a combined adversary  $A^*$ , we can show that:

---

$$\Pr [\text{View}\langle \mathcal{A}, \text{ConComp}(\mathcal{M}_0(x'), \dots, \mathcal{M}_{i-1}(x'), \mathcal{M}_i(x), \dots, \mathcal{M}_{k-1}(x)) \rangle \in S] \\ \leq e^{\epsilon_i} \Pr [\text{View}\langle \mathcal{A}, \text{ConComp}(\mathcal{M}_0(x'), \dots, \mathcal{M}_{i-1}(x'), \mathcal{M}_i(x'), \dots, \mathcal{M}_{k-1}(x)) \rangle \in S] + \delta_i$$



# Group Privacy-like Bound

$$\begin{aligned} & \Pr [\text{View}\langle \mathcal{A}, \text{ConComp}(\mathcal{M}_0(x), \mathcal{M}_1(x), \dots, \mathcal{M}_{k-1}(x)) \rangle \in S] \\ & \leq e^{\varepsilon_0} \Pr [\text{View}\langle \mathcal{A}, \text{ConComp}(\mathcal{M}_0(x'), \mathcal{M}_1(x), \dots, \mathcal{M}_{k-1}(x)) \rangle \in S] + \delta_0 \\ & \leq e^{\varepsilon_0} (e^{\varepsilon_1} \Pr [\text{View}\langle \mathcal{A}, \text{ConComp}(\mathcal{M}_0(x'), \mathcal{M}_1(x'), \dots, \mathcal{M}_{k-1}(x)) \rangle \in S] + \delta_1) + \delta_0 \\ & \leq \dots \\ & \leq e^{\sum_{i=0}^{k-1} \varepsilon_i} \Pr [\text{View}\langle \mathcal{A}, \text{ConComp}(\mathcal{M}_0(x'), \mathcal{M}_1(x'), \dots, \mathcal{M}_{k-1}(x')) \rangle \in S] \\ & \quad + \underbrace{(\delta_0 + e^{\varepsilon_0} \delta_1 + e^{\varepsilon_0 + \varepsilon_1} \delta_2 + \dots + e^{\sum_{i=0}^{k-2} \varepsilon_i} \delta_{k-1})}_{\text{Same bound for Group Privacy}} \leq k e^{\sum_{i=0}^{k-1} \varepsilon_i} \max_i(\delta_i). \\ & \quad = \left( 1 + e^\varepsilon + e^{2\varepsilon} + \dots + e^{(k-1)\cdot\varepsilon} \right) \cdot \delta \end{aligned}$$

Same bound for Group Privacy

Group Privacy-like Bound

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# Characterization of Concurrent Composition

- Randomized Response

$RR_{(\epsilon, \delta)} : \{0, 1\} \rightarrow \{0, 1, \text{'Iam0'}, \text{'Iam1'}\}$  is  $(\epsilon, \delta)$ -DP

$$\begin{array}{ll} \Pr \left[ RR_{(\epsilon, \delta)}(0) = \underline{\text{'Iam0'}} \right] = \delta & \Pr \left[ RR_{(\epsilon, \delta)}(1) = \text{'Iam0'} \right] = 0 \\ \Pr \left[ RR_{(\epsilon, \delta)}(0) = 0 \right] = (1 - \delta) \cdot \frac{e^\epsilon}{1 + e^\epsilon} & \Pr \left[ RR_{(\epsilon, \delta)}(1) = 0 \right] = (1 - \delta) \cdot \frac{1}{1 + e^\epsilon} \\ \Pr \left[ RR_{(\epsilon, \delta)}(0) = 1 \right] = (1 - \delta) \cdot \frac{1}{1 + e^\epsilon} & \Pr \left[ RR_{(\epsilon, \delta)}(1) = 1 \right] = (1 - \delta) \cdot \frac{e^\epsilon}{1 + e^\epsilon} \\ \Pr \left[ RR_{(\epsilon, \delta)}(0) = \text{'Iam1'} \right] = 0 & \Pr \left[ RR_{(\epsilon, \delta)}(1) = \underline{\text{'Iam1'}} \right] = \delta \end{array}$$



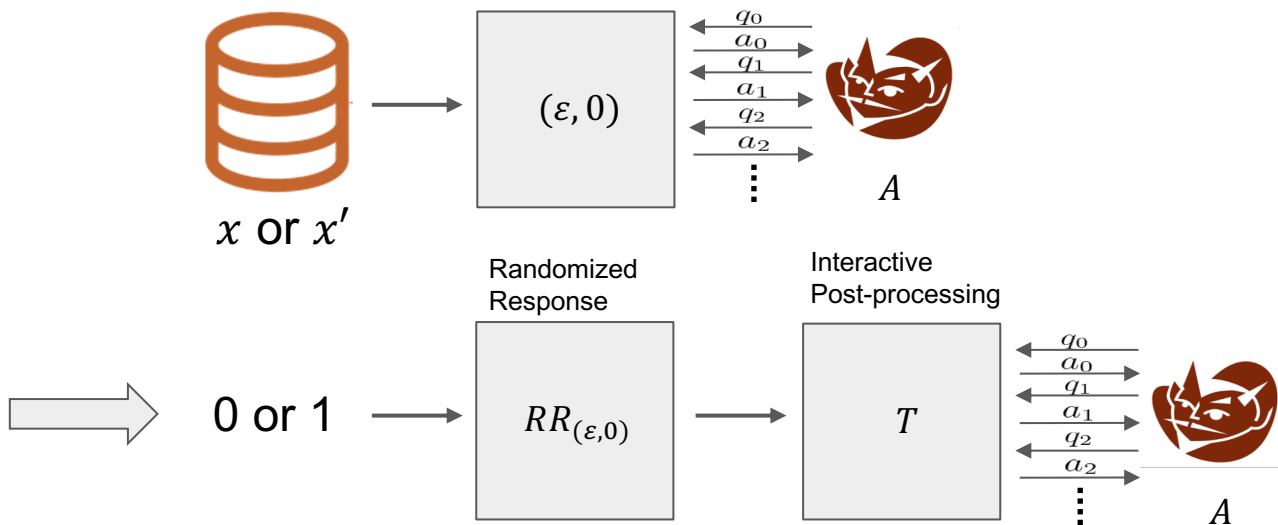
# Characterization of Concurrent Composition

- For **every** non-interactive  $(\epsilon, \delta)$  –DP algorithms and every neighboring dataset  $x_0 \sim x_1$ , there exists a post-processing  $T$  of randomized response  $RR_{(\epsilon, \delta)}$  such that  $T(RR_{(\epsilon, \delta)}(b))$  is identically distributed to  $M(x_b)$  [KOV15, MV17].
- Post-processing preserves differential privacy  
=>To analyze the composition of arbitrary non-interactive DP algorithms, it suffices to analyze the composition of  $RR$ 's.
- If we are able to prove a similar result for interactive differential privacy, then we will be able to extend all results of composition theorem for non-interactive mechanisms to interactive mechanisms!



# Characterization of Concurrent Composition

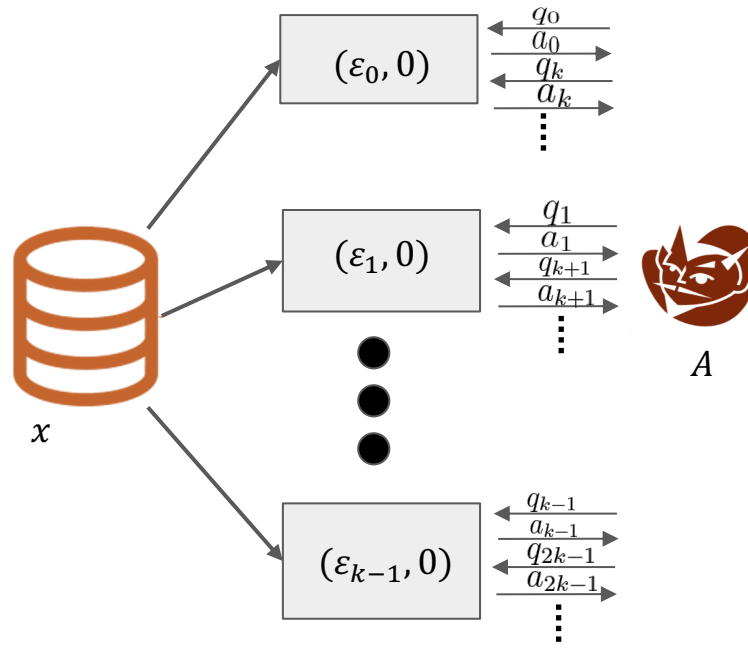
- **Every** interactive  $(\varepsilon, 0)$  –DP mechanisms can be simulated as the post-processing of randomized response  $RR_{(\varepsilon,0)}$ .



# Characterization of Concurrent Composition

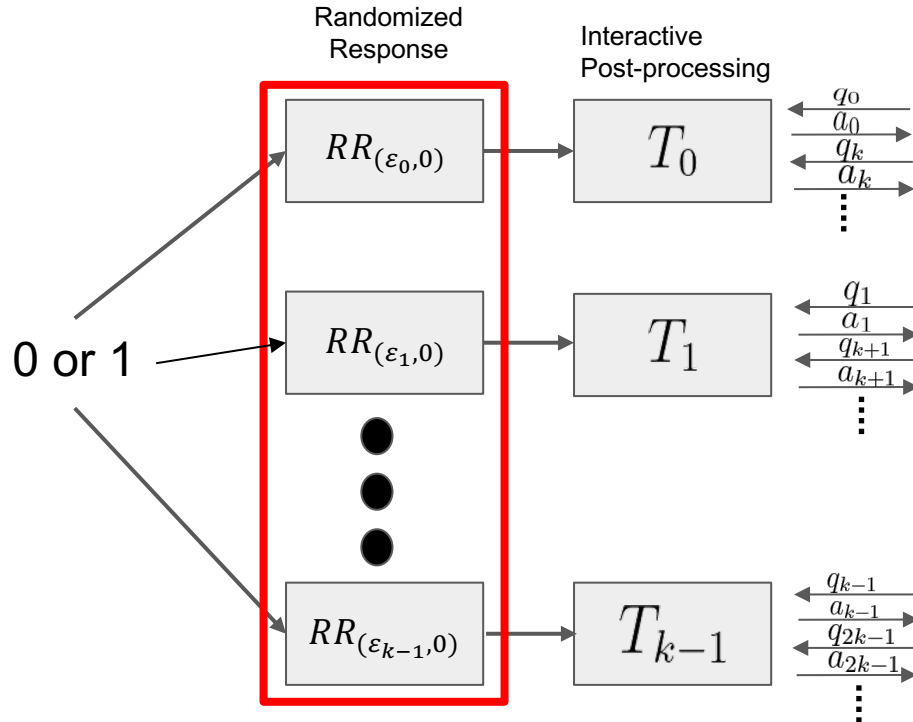


- **Every** interactive  $(\varepsilon, 0)$  –DP mechanisms can be simulated as the post-processing of randomized response  $RR_{(\varepsilon,0)}$ .





# Characterization of Concurrent Composition



A



# Characterization of Concurrent Composition

- If interactive mechanism  $M_0, \dots, M_{k-1}$  are each  $(\varepsilon_i, 0)$ -DP for  $i = 0..k-1$ , then given a target  $\delta_g$ , the privacy parameter of the current composition  $ConComp(M_0, \dots, M_{k-1})$  is tightly upper bounded by the least value of  $\varepsilon_g$  such that

$$\frac{1}{\prod_{i=0}^{k-1} (1 + e^{\varepsilon_i})} \sum_{S \subseteq \{0, \dots, k-1\}} \max \left\{ e^{\sum_{i \in S} \varepsilon_i} - e^{\varepsilon_g} \cdot e^{\sum_{i \notin S} \varepsilon_i}, 0 \right\} \leq \delta_g$$

(Optimal Bound from MV17 for non-interactive DP)

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# Empirical Findings & Future Work

- We find empirical evidence supports that the Optimal Composition Theorems from [KOV15] can be extended to the concurrent composition of approximate DP mechanisms.
  - We evaluate whether any 2-round  $(\epsilon, \delta)$  interactive mechanisms with 1-bit messages can be simulated by some interactive post-processing of randomized response.

